RESEARCH ON DETECTION OF SPARTINA ALTERNIFLORA BASED ON SA-YOLO
/
基于 SA-YOLO 的互花米草识别算法研究

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ABSTRACT
In view of the difficulty and high cost of monitoring the invasion of small aggregations of Spartina alterniflora in coastal wetlands, this study proposes a SA-YOLO detection model. First, by adopting a lightweight cascade attention mechanism as the feature extraction part of the network, the model's ability to extract features from Spartina alterniflora images is optimized. Secondly, the convolution layer with an improved adaptive attention mechanism is added to optimize feature extraction, dynamically adjust the weight of the feature map, and reduce the amount of calculation. Thirdly, the improved adaptive convolution network is used to optimize the original neck layer, improve the model's ability to integrate Spartina alterniflora image features, and reduce the amount of calculation. Finally, a Spartina alterniflora recognition system is independently built. The system effectively implements the proposed method and realizes the detection and recording of Spartina alterniflora information. This study successfully verifies the effectiveness of the proposed method by conducting experiments on the actual collected Spartina alterniflora dataset. The test results show that the recall rate and accuracy of the proposed SA-YOLO Spartina alterniflora detection model are 94.5% and 92.4%, respectively, both reaching a high level. It can be seen that the model can complete the identification and detection tasks of Spartina alterniflora, providing a solution for the identification and information collection of Spartina alterniflora in coastal areas.

摘 要
针对滨海湿地小聚集互花米草入侵监测难度大、成本高的问题，本研究提出了 SA-YOLO 检测模型。首先，通过采用轻量级级联注意力机制作为网络的特征提取部分，优化模型对互花米草图像特征提取能力；其次，加入改进自适应注意力机制的卷积层优化特征提取，动态调整特征图权重，降低计算量；再者，采用改进的自适应卷积网络对原有的 neck 层进行优化，提高模型融合互花米草图像特征的能力，降低计算量。最后，自主搭建了互花米草识别系统。该系统有效实施了提出的方法，实现了互花米草信息的检测与记录。本研究通过在实际采集的互花米草数据集上进行实验，成功验证了所提方法的有效性。测试结果表明，所提出的 SA-YOLO 互花米草检测模型的召回率和准确率分别为 94.5%和 92.4%，均达到较高水平。可见该模型能够完成互花米草的识别检测任务，为沿海地区互花米草识别与信息采集提供了一种解决方案。

INTRODUCTION
Spartina alterniflora is an important coastal wetland plant and a typical invasive alien species. It was introduced into China in 1979 (*Jin et al., 2024*). Spartina alterniflora has a well-developed root system, mainly composed of underground stems and adventitious roots, which are widely distributed in the soil. On the one hand, this gives Spartina alterniflora good soil fixation and growth capabilities; on the other hand, it compresses the living environment of local species, easily causing damage to the local ecosystem and reducing species diversity. In addition, Spartina alterniflora has strong reproductive capacity and grows rapidly. One is sexual reproduction, through the random drift of seeds, it begins to take root and grow when it encounters a suitable environment; the other is asexual reproduction through rhizome diffusion, which allows Spartina alterniflora to expand its population in a short period of time. The growth and reproduction characteristics of Spartina alterniflora increase the difficulty and uncertainty of its prevention and control, and it is difficult to grasp its growth location, time and other factors (*Feng et al., 2024*). As shown in Figure 1, this is the growth and distribution map of Spartina alterniflora in China produced by the Key Laboratory of Biodiversity and Ecological

Engineering of the Ministry of Education of Fudan University.

The growth environment of Spartina alterniflora is mainly in coastal wetlands, including intertidal zones of coastal mudflats such as estuaries and bays, and river beaches affected by tides (*Li et al., 2024*). These areas are complex and difficult to access, which facilitates the random growth of Spartina alterniflora (*Zhang et al., 2024*). At the same time, it is also the growth environment of reeds and other aquatic herbs. Spartina alterniflora is similar to reeds in appearance, but there are also significant differences between the two (*Qiu et al., 2022*). Spartina alterniflora has long leaf lines and rough edges. Because of its secretion characteristics, its leaf surface often has white powdery salt frost, so it has good salt tolerance (*Ma et al., 2010*). Only by achieving effective monitoring and management of Spartina alterniflora can it be beneficial to maintain the local ecological balance and protect the coastal wetland environment. The development of drone technology and the rapid update of computer vision have provided high-quality methods for monitoring. Neural network recognition can reduce the influence of subjective factors, save costs, eliminate accurate positioning, and improve the accuracy of recognition results (*Qiu et al., 2022*).

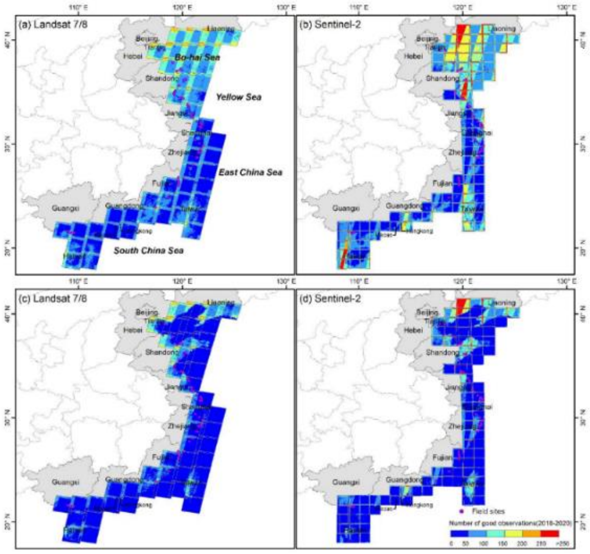


Fig. 1 – Distribution map of Spartina alterniflora in China

Tian et al. (*2020*) used the Zhangjiangkou National Nature Reserve in Fujian as the study area. Based on field surveys and drone aerial photography, they obtained training and validation samples of Spartina alterniflora for remote sensing image classification, and collected time series Sentinel-2 images of the start and end dates of the growing season in the study area from 2016 to 2018. Based on the spectral reflectance curves of different landform types in Sentinel-2 images, the vegetation index for extracting submerged Spartina alterniflora was established by using the characteristics of large differences in reflectance between submerged Spartina alterniflora pixels and pure water surface pixels in the red edge band. Then, an object-oriented random forest classification method was used to interpret Spartina alterniflora in the study area from 2016 to 2018. The seasonal expansion information of Spartina alterniflora was extracted, and the interpretation accuracy reached more than 92%. *Li et al. (2024)* conducted a hyperspectral inversion study on the functional traits of Spartina alterniflora in the Yancheng coastal wetland, confirming the great potential of hyperspectral technology in estimating functional traits. The accuracy and stability of the support vector machine constructed by selecting feature bands based on random forest importance score in inverting the functional traits of Spartina alterniflora leaves were verified. *Zheng Hao et al., (2023),* used the Sentinel-2 NDVI dataset to obtain the vegetation phenology information of the study area in the core area of Yancheng Wetland Rare Bird National Nature Reserve, and identified the key phenological period for Spartina alterniflora extraction. Then, based on the multi-source and multi-temporal remote sensing data in the key phenological period, a feature set was constructed, and the landscape classification map was obtained by using five methods, ResNet18, MSRN2, CDCNN, SVM, and RF, and the accuracy was evaluated. *Zhu et al., (2020),* combined deep learning with remote sensing data to achieve high-precision classification and dynamic monitoring of Spartina alterniflora in the coastal areas of Shandong Province.

Based on YOLOv8n, this study proposed an algorithm with high detection accuracy and fast detection speed, and actually deployed it on a self-built server to achieve timely monitoring and analysis of the growth of Spartina alterniflora, reduce the input of manpower and material resources, and provide solution experience for the application of machine vision in the field of agricultural engineering.

MATERIALS AND METHODS

Data Acquisition and Pre-processing

The Spartina alterniflora dataset for this experiment was collected through web crawlers and field photography of some coastal wetlands, estuaries and river estuaries in Shandong Province. Images were collected from different angles, distances and time points. The collection equipment included mobile phones, Nikon Z30 micro-single cameras, etc. After screening and deletion, a total of 357 original images were obtained. In the actual dataset collection process, the image collection time was summer and autumn, so the dataset was divided into two categories of Spartina alterniflora in summer and autumn. The data set required for this experiment was enhanced by data enhancement and CutMix data processing under the Opencv library, and the original 357 images were enhanced to 1755 images by image translation, rotation, mirroring, and adjusting contrast and brightness, as shown in Figure 2.

After data enhancement, the LabelImg image annotation tool was used to annotate the images. They were divided into two major categories: summer Spartina alterniflora and autumn Spartina alterniflora, and the image annotation information file xml file was obtained, which was then converted into a txt format suitable for YOLO.

To meet the requirements for fast acquisition, processing, and recognition of Spartina alterniflora, this paper improves the original YOLOv8 network to achieve faster recognition and detection while improving detection speed and accuracy.

Spartina alterniflora recognition based on YOLOv8

The YOLOv8(*Github.com*) image recognition model consists of an input layer (Input), a backbone layer (Backbone), a bottleneck layer (Neck) and an output layer (Output). The image of Spartina alterniflora enters the Input and undergoes a batch resize operation to ensure the size consistency of the input image. The main network of SA-YOLO is used to extract features from images. The main network of the SA-YOLO model uses the cascaded attention mechanism EfficientVit (*Cai et al., 2022*) as the basic structure to complete the feature extraction of the Spartina alterniflora image. It mainly consists of four stages. The size of the feature map from input to output gradually decreases, forming a feature pyramid. First, the standard convolution layer performs upsampling preparation to extract the basic features of the Spartina alterniflora image; then, the image is subjected to deep convolution and weighted processing through a feature extraction module consisting of two MBConv modules, which helps capture the feature information of Spartina alterniflora in the image; finally, the image enters the two-layer EfficientVit Block module, which adopts a sandwich layout, uses MHSA (multi-head self-attention mechanism), and realizes channel information enhancement through parameter redistribution, strengthening the model's extraction of global information and local details of Spartina alterniflora. SPPF extracts the global feature information of Spartina alterniflora and performs global maximum pooling to enhance the receptive field. The feature fusion of the Neck part is enhanced, and the C2f convolution layer is optimized to DCNv4 *(Xiong et al., 2024).* This module has excellent expression and computing capabilities for complex backgrounds, and strengthens the model's feature expression and information extraction of Spartina alterniflora images. The SA-YOLO model structure is shown in Figure 2.

(a) Data Collection

Original image | Crop the image | Brightness Adjustment | Mirror | Add Noise | Rotation

(b) Data Augmentation

Fig. 2 - Dataset

SA-YOLO network improvement

This paper takes YOLOv8 as the basic model and proposes SA-YOLO for the growth environment and plant information elements of Spartina alterniflora. First, the lightweight EfficientVit network is used to replace the backbone to enhance the model's perception and feature extraction capabilities for higher-resolution images and expand the model's receptive field; when extracting features, the DCNv4 module is introduced to further reduce the model's computational workload while enhancing the model's feature fusion and expression capabilities, making the model more real-time and accurate while being lightweight. Compared with the original model, the improved SA-YOLO algorithm is not only lightweight, but also has higher computational efficiency and recognition accuracy.

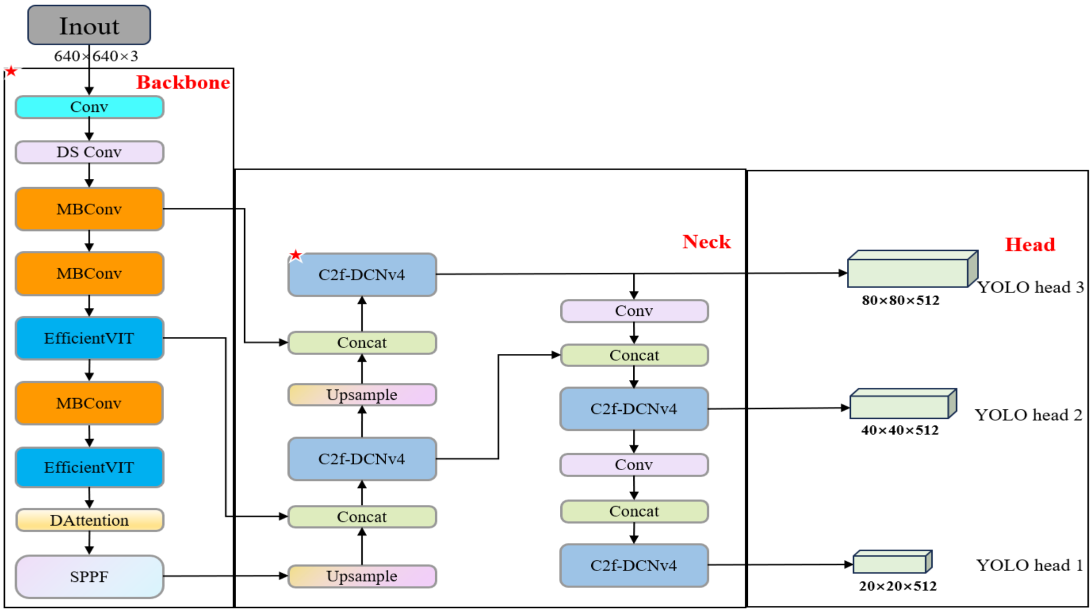


Fig. 3 -SA-YOLO Model structure

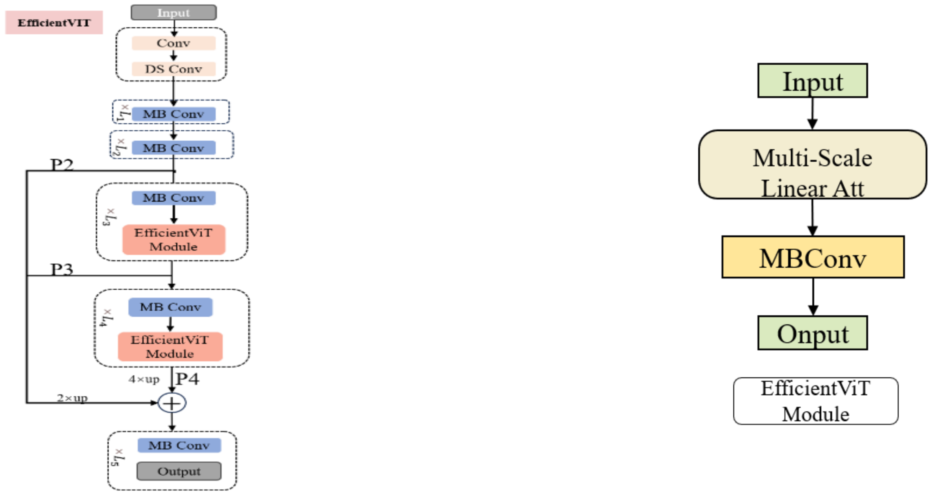
During the improvement process, the aim was to make the model have high-precision detection capability and strong feature extraction level for the input Spartina alterniflora images. The cascaded attention mechanism EfficientViT is introduced to replace the backbone network, so that the model has fast computing capabilities while maintaining high-precision detection. EfficientViT is a Vision transformer model for high-resolution dense prediction proposed by Cai et al., as shown in Figure 4 (a). By using ReLU linear attention to achieve global receptive field, lightweight and hardware-efficient operations can achieve the purpose of global receptive field and multi-scale learning.

EfficientViT uses EfficientViT block as the core module, as shown in Figure 4 (b), which consists of a sandwich structure (Sandwich Layout) and cascaded group attention (Cascaded Group Attention, CGA), that is, a lightweight MSA module and an MBConv module. This basic module reduces the use of attention and alleviates the problem of memory access time consumption caused by attention calculation. At the same time, a layer of DWConv is added before each FFN as information interaction between local tokens and helps introduce inductive bias. The lightweight MSA module is mainly used to enhance the feature representation ability of the model, and plays an important role in the feature extraction and expression of Spartina alterniflora images in complex environments.

As shown in Figure 5, the lightweight MSA module *(Rao et al., 2021)* first performs multi-scale processing on the input Spartina alterniflora feature map to obtain feature representations of multiple scales, which cover different aspects from local details to global context information. Then, the ReLU linear attention mechanism is used to assign weights to these multi-scale features. After obtaining the weights, the lightweight MSA module applies these weights to the original multi-scale feature map for weighted fusion. Finally, the feature map processed by the lightweight MSA module will be sent to the subsequent network layer for further processing and prediction.

As shown in Figure 6, the MBConv module *(Mark et al., 2018)* mainly consists of a 1x1 convolution layer (for dimensionality increase or decrease), a depthwise separable convolution, and a 1x1 pointwise convolution. The 1x1 convolution layer in MBConv plays the role of dimensionality increase and dimensionality reduction.

As the core part of MBConv, the depthwise separable convolution applies a convolution kernel to each channel of the input feature map, and then fuses the information between channels of the output of the depthwise convolution through a 1x1 point-by-point convolution. Each convolution layer is usually followed by an activation function (ReLU6 *(Mansuri et al., 2022)* and a batch normalization layer. The activation function can increase the nonlinearity of the model and improve the expressiveness of the model, while batch normalization helps to accelerate the training process of the model and improve the stability of the model.



(a) EfficientViT *(b) Efficient block*

Fig. 4 - EfficientViT Model

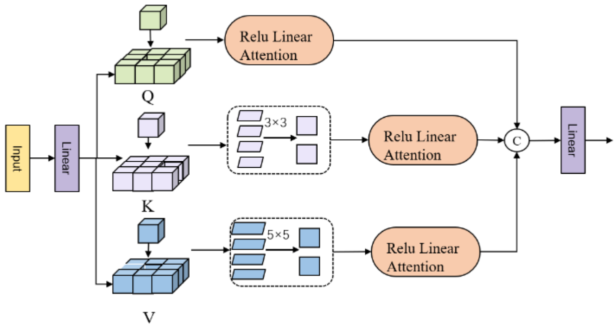


Fig. 5 -Lightweight MSA Module

Fig. 6 - MBConv Model

C2f-DCNv4 convolution optimization

DCNv4 is a new type of deformable convolution network architecture. It adjusts the size of the convolution kernel by understanding different learnable offsets, so that the network focuses on the position and shape of Spartina alterniflora in the image. Compared with the previous generation, DCNv4 is optimized in two ways: when performing spatial aggregation, it no longer uses Softmax normalization processing and adopts a more flexible weight adjustment strategy; second, it adopts dynamic feature enhancement to convert the modulated scalar between 0 and 1 into an unbounded dynamic weight like convolution. The main structure of DCNv4 includes DCNv4Conv layer, batch normalization module and SiLU activation function *(Jocher et al., 2021)*. After inputting the feature map, the channels are first grouped, where the input feature x∈R^(H×W×C) (height H, width W and number of channels C), then each group is convolved to obtain the offset and weight, and finally the convolution results of all groups are spliced and output.

The output p_0 is calculated as follows:

$$y_g = \sum_{k=1}^{k} m_{gk} x_g(p_0 + p_k + \Delta p_{gk}) \quad (1)$$

$$y = concat([y_1, y_2, \cdots y_G]) \tag{2}$$

where: x_g and y_g represent the input features and corresponding output features of the g group respectively; m_{gk} represents the weight of the k-th sample point in the g group; p_k represents the k key node in the basic network; Δp_{gk} represents the offset relative to the basic network p_k; $concat$ represents the increase in the number of image feature descriptions.

The optimized structure of the C2f-DCNv4 module is shown in Figure 7. By introducing DCNv4 into C2f, the detection of Spartina alterniflora in complex growth environments is significantly improved, and it adapts to different changes in image sizes, thereby improving detection accuracy and robustness.

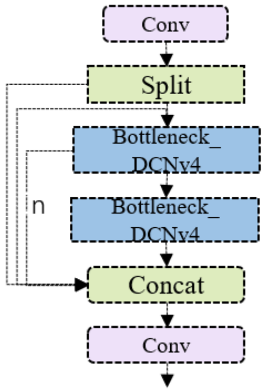


Fig. 7 - C2f_DVNv4 Model

Model deployment and hardware integration

This study conducted a field test on the proposed SA-YOLO model, and built a Spartina alterniflora recognition system based on the Flask framework and OpenCV to achieve real-time monitoring, target detection and statistical analysis of Spartina alterniflora in wetland environments.

This study tested non-dataset images collected in the field of Spartina alterniflora. Some of them were uploaded to the server locally after being taken by mobile phones and cameras, ensuring data security, preservation and reducing costs, and some were uploaded to the server in real time after being taken by drones. The server uses Flask as the backend framework and integrates the SA-YOLO model for target detection. During real-time uploading, in order to ensure efficient data transmission and real-time processing, data transmission supports Real Time Streaming Protocol (RTSP), which can push video streams to the server to achieve low-latency video processing and analysis.

As shown in Figure 8, the server receives the uploaded image. Subsequently, the system uses the SA-YOLO model for target detection. The processed detection results are re-encoded and pushed to the client through Flask's multipart/x-mixed-replace streaming transmission to achieve real-time monitoring and result display.

On the client side, users can view the identified video stream through a web browser and perform area annotation, target statistics, and parameter adjustments. In addition, the system provides historical data analysis and visualization functions, which can generate trend charts to analyze the growth distribution and changes of Spartina alterniflora, providing data support for ecological environment monitoring and governance.

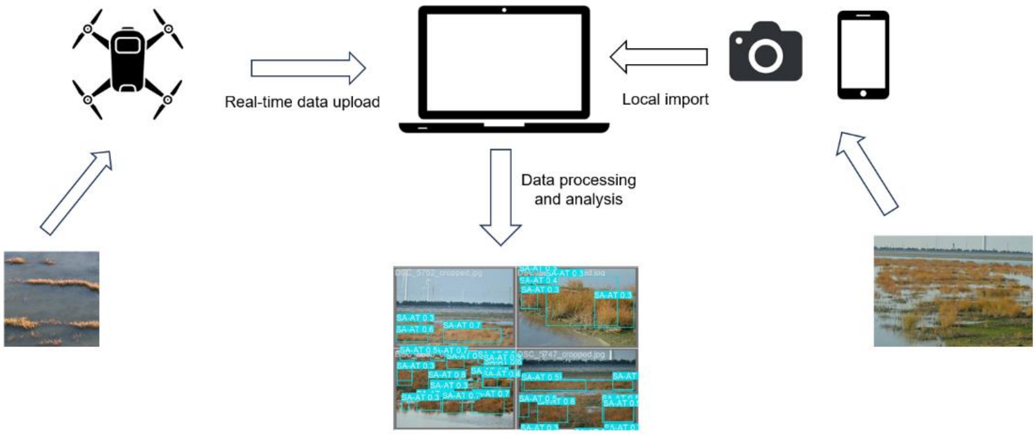


Fig. 8 - Working diagram of Spartina alterniflora identification system

RESULTS

The experiments and server deployments in this study were trained under the Windows 11 operating system. The CPU used was Intel i7-12600H, the GPU was NVIDIA RTX 3060 graphics card with 8 GB of video memory, the host memory was 16 GB, and the CUDA version was 11.8.

During the training process, according to the actual situation of the equipment, the batch size was set to 16, the number of process workers was set to 8, Adam with weight decay (AdamW) was used as the optimizer, the learning rate was set to 0.01, the momentum was set to 0.937, the weight decay coefficient was set to 0.1, and the number of training rounds was set to 300.

Model evaluation indicators

In order to fully verify the model's ability to identify and detect Spartina alterniflora, as well as the improved model's ability, precision P (Precision), recall R (Recall), and mean average precision (mAP) were used as indicators for evaluating the model.

The precision P represents the proportion of correctly predicted samples in all samples, as shown in Eq.(3):

$$P = \frac{T_P}{Tp+F_P} \times 100\% \tag{3}$$

The recall rate R represents the proportion of correctly predicted samples in all positive samples, as shown in formula (4):

$$R = \frac{T_P}{T_P+F_N} \times 100\% \tag{4}$$

The average precision mAP is the mean of the average precision (AP), and the average precision AP is the area of the P-R curve, as shown in formula (5):

$$mAP = \frac{\sum_{i=1}^{N}\int_0^1 P(R)dR}{N} \times 100\% \tag{5}$$

In the formula, T_P represents the number of correctly predicted positive samples, F_P represents the number of incorrectly predicted positive samples, F_N represents the number of incorrectly predicted negative samples, and N represents the number of categories. In this study, two categories of Spartina alterniflora are discussed, so N=2 at this time.

Ablation Experiment

In order to verify the model effect after replacing the backbone, the optimization degree of the model after adding the self-attention mechanism, and the effect of model feature fusion after adding deformable convolution, an ablation experiment was conducted.

Table 1

Ablation Experiment

	EfficientVit	DAttention	C2f_DCNv4	P（%）	R（%）	mAP（%）
YOLOv8				89.3	87.1	90.2
1	√			90.4	89.6	92.1
2		√		88.1	86.9	90.5
3			√	89.6	88.2	91.8

4	√	√		89.7	88.6	91.7
5	√		√	91.3	90.7	92.6
6		√	√	91.5	90.8	92.2
SA-YOLO	√	√	√	92.4	94.5	93.1

Through ablation experiments, it can be seen that after replacing the backbone network, the accuracy, recall and average precision of the model in Spartina alterniflora recognition have all improved, indicating that the model has improved the feature extraction and receptive field of Spartina alterniflora. After replacing the deformable convolution, the model's detection ability has been further improved, as reflected in the accuracy and recall rates increased by 0.9% and 1.1% respectively, and the average precision value increased by 2.1%. Overall, the SA-YOLO algorithm proposed in this study is optimal.

Comparison of detection results by model

To verify the advantages of the improved model, it is compared with the original YOLOv8, YOLOv5, and YOLOv3. The performance comparison of different models is shown in Table 2.

Table 2

Detection Results Of Different Models On Spartina Alterniflora

Model	Precision（%）	Recall（%）	mAP（%）
YOLOv8	89.3	87.1	90.2
YOLOv5	86.7	86.4	88.4
YOLOv3	85.1	85.3	87.6
SA-YOLO	92.4	94.5	93.1

As shown in Table 2, the accuracy and recall of the SA-YOLO model are both above 90%. In terms of accuracy, compared with the original YOLOv8, YOLOv5, and YOLOv3 networks, they are improved by 3.1%, 5.7%, and 7.3%, respectively. In terms of recall, SA-YOLO is 94.5%, which is improved to varying degrees compared with YOLOv8, YOLOv5, and YOLOv3, by 7.4%, 8.2%, and 9.2%, respectively. In terms of average precision, SA-YOLO is 2.9%, 4.7%, and 5.5% higher than YOLOv8, YOLOv5, and YOLOv3, respectively. From the comprehensive data, SA-YOLO has a significant improvement in the overall performance of the model, which is better than the other three models.

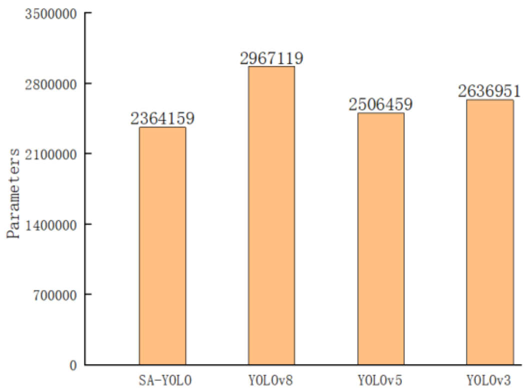


Fig. 9 - Comparison of parameters of each model

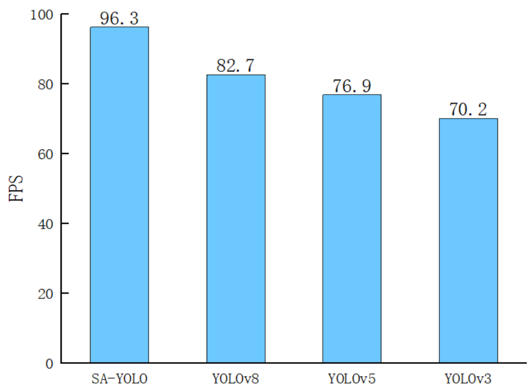


Fig. 10 – Comparison of detection speed FPS of each model

In Figures 9 and 10 the number of parameters and detection speed of different models in the process of detecting Spartina alterniflora is shown. Obviously, the SA-YOLO model generates fewer parameters during the detection process, but the detection speed and accuracy are far superior to other models. As shown in Figure 11, the detection results of Spartina alterniflora by the improved model have reached a higher level. Figure 12 shows the comparison of the recall rate and accuracy of YOLOv8 before and after the improvement.

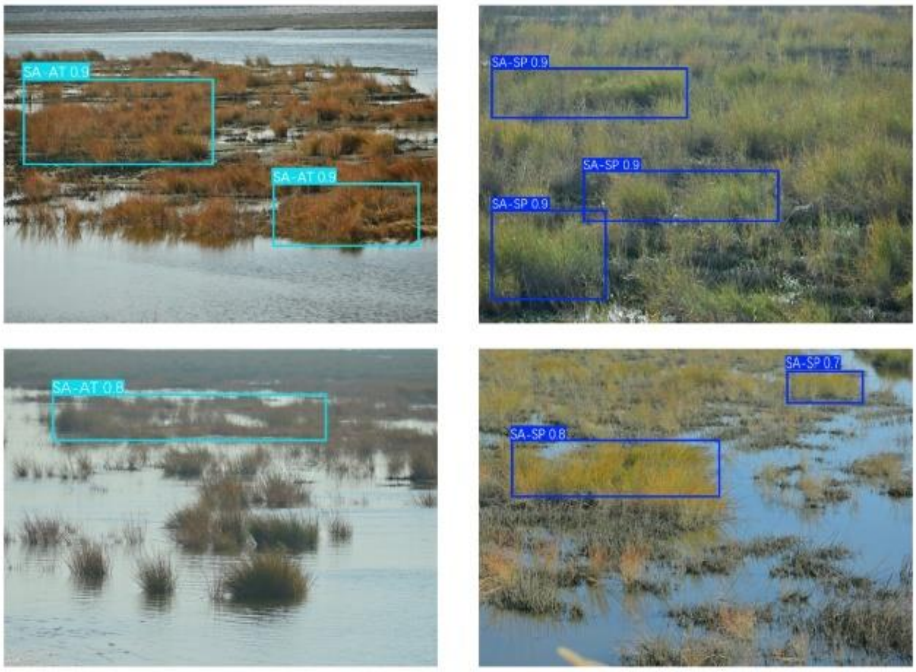


Fig. 11 –Some test results

The improved SA-YOLO model has better convergence ability and higher accuracy, which shows the effectiveness of the model improvement, especially after adding the cascaded attention mechanism and variable convolution, the model has better receptive field and recognition ability.

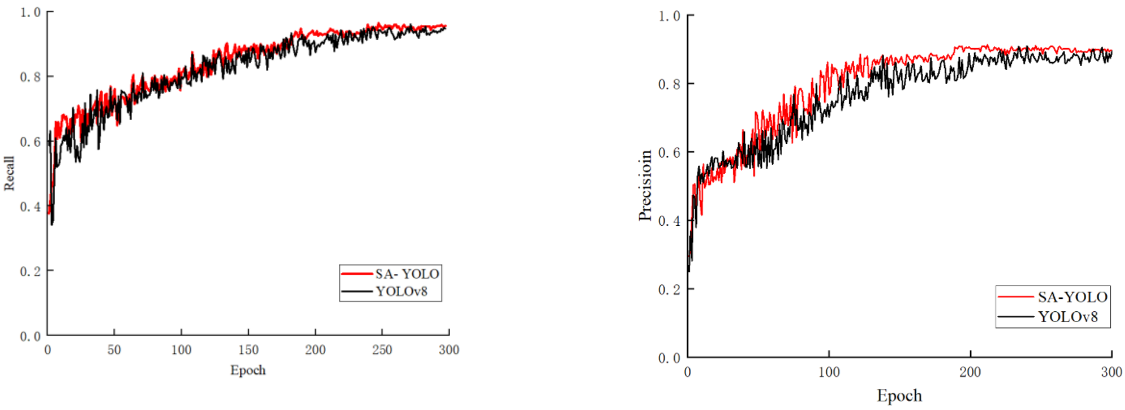


Fig. 12 – Recall and precision curve results

Comparison of the recognition and detection capabilities of each model for Spartina alterniflora in summer and autumn

As shown in Tables 3 and 4, the performance comparison of each model for the recognition of Spartina alterniflora in summer and autumn is shown.

Table 3

Detection Results of Different Models for Spartina Alterniflora in Summer

Model	Precision（%）	Recall（%）	mAP（%）
YOLOv8	90.5	89.6	93.5
YOLOv5	87.3	88.7	90.2
YOLOv3	86.7	87.2	89.5
SA-YOLO	93.1	91.6	95.4

Table 4

Detection Results of Different Models for Spartina Alterniflora in Autumn

Model	Precision（%）	Recall（%）	mAP（%）

YOLOv8	88.6	88.2	91.3
YOLOv5	87.5	89.1	89.3
YOLOv3	87.3	88.0	89.1
SA-YOLO	91.6	92.5	94.8

As shown in Tables 3 and 4, in the detection of data sets taken in different seasons but under the same weather conditions, the detection effects of each model for Spartina alterniflora in both seasons are good.

In the recognition of Spartina alterniflora in summer, the accuracy, recall rate and average detection precision of the SA-YOLO model are higher than those of the other three groups of models. The accuracy is 2.6%, 5.8% and 6.4% higher than YOLOv8, YOLOv5 and YOLOv3 respectively, and the recall rate is 2.0%, 2.9% and 4.4% higher respectively. The average precision is 1.9%, 5.2% and 5.9% higher respectively, which fully demonstrates that the proposed SA-YOLO model has the ability to detect Spartina alterniflora.

In the recognition of Spartina alterniflora in autumn, the expressiveness is not as good as that in summer, mainly because Spartina alterniflora grows more vigorously in summer, first of all, it has more characteristics in appearance, and secondly, it is also very different from the surrounding environment. In contrast, Spartina alterniflora in autumn is yellow in color and has sparse branches and stems, which is more integrated with the surrounding environment. However, SA-YOLO still has good recognition and detection capabilities. In terms of accuracy, it is 3.0%, 4.1%, and 4.3% higher than YOLOv8, YOLOv5, and YOLOv3, respectively. In terms of recall, it is 4.3%, 3.4%, and 4.5% higher, and in terms of average precision, it is 3.5%, 5.5%, and 5.7% higher.

System testing and effect evaluation

This study conducted multiple tests of the Spartina alterniflora information collection and identification system in November 2024 to verify the proposed SA-YOLO model for the Spartina alterniflora clusters in the coastal wetland area. As shown in Figure 13, it is an information image of Spartina alterniflora that was taken by a camera and uploaded locally by a computer.

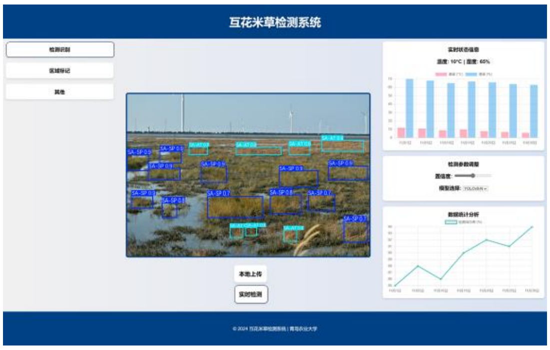


Fig. 13 – Demonstration of the local upload effect of the Spartina alterniflora identification system

As shown in Figure 14, this study shows the effect of using drones to capture image pairs and achieve real-time uploading and processing. During the experiment, the drone and the computer were in the same Wi-Fi network to ensure the stability and real-time performance of data transmission.

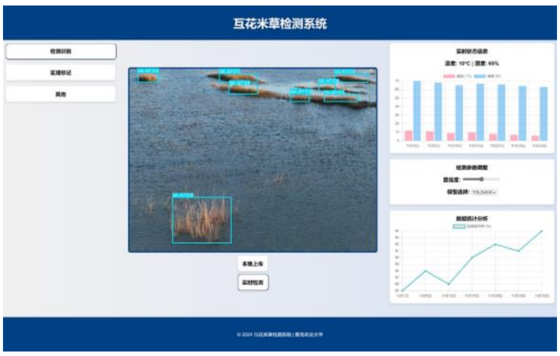


Fig. 14– Real-time upload effect display of Spartina alterniflora identification system

CONCLUSIONS

The improved Spartina alterniflora detection model SA-YOLO based on YOLOv8 proposed in this study was trained and tested with a self-made dataset, which fully verified the effectiveness of the improvement. Multiple comparative tests were conducted, and the results showed that while SA-YOLO is lightweight, it has good performance in detection speed and accuracy of Spartina alterniflora. Its recall and accuracy reached 94.5% and 92.4%, and the mAP value of detection was 93.1%. Its comprehensive performance is higher than that of the original YOLOv8, YOLOv5, and Faster R-CNN.

In addition, this study also verified the actual deployment of the model, developed a Spartina alterniflora identification system, and conducted multiple field tests in stages. The results showed that both the Spartina alterniflora information images uploaded via the Internet and locally had good processing results and records.

Looking back at the entire research process, although the recognition and detection of Spartina alterniflora was achieved well, there is still room for improvement. First, the establishment of the Spartina alterniflora data set still needs further improvement; second, in terms of model deployment, there is a lot of room for server-side function expansion; third, you can try to combine the model with the Spartina alterniflora elimination machine.

This research is of great significance for the identification and detection of Spartina alterniflora, and is of great significance for future intelligent prevention and control of Spartina alterniflora, protection of the ecological environment and ecological diversity.

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[20] ***Ultralytics/ultralytics: NEW - YOLOv8 in PyTorch > ONNX > OpenVINO > CoreML > TFLite (Github.com)